Adapting to Groups of Learners

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Almost all work on adaptive systems to date focuses on adapting to individual learners. However, there are many situations when it would be good if we could adapt to a group of learners rather than to an individual. For instance, learners may have to share a device, as is often the case in interactive Television (which tends to be viewed in groups), and ambient intelligent environments. A teacher may also want a group of learners to share their learning experience, as some pedagogical theories emphasize the role of learning together. For instance, Lave and Wenger's concept of "situated learning" promotes the notion that learning takes place from the process of engagement in a community of practice [1], which may be a classroom community. A related approach is Vicarious Learning [2], which asserts that people can benefit from observing and modelling the behaviours, attitudes and emotional reactions of other learners. Also, social-constructivism emphasises the benefits of learning in engagement with others. This raises questions on how to select activities that will benefit the group as a whole. In this presentation, we will draw from our experiences in group recommender systems, and attempt to show how these can be applied to adaptive e-learning.

Adapting to groups is even more complicated than adapting to individuals. In this presentation, we will discuss how group adaptation works, what its problems are, and what advances have been made. Interestingly, we will show that group adaptation techniques have many uses as well when adapting to individual learners.

The main problem group adaptation needs to solve is how to adapt to the group as a whole based on information about what is good for individual users. For instance, suppose the group contains three people, Peter, Jane and Mary. Suppose a system is aware that these three individuals are present and knows how good each of a set of items is for them (e.g. lessons, activities). Table 1 gives example ratings on a scale of 1 (really bad) to 10 (really good). Which items should the system select, given time for four items?

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<th>A</th>
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Table 1. Example of individual ratings for ten items (A to J)

Many different strategies exist for aggregating ratings of individuals into a rating of a group (e.g. used in elections, like when selecting the leader of a political party). Eleven of these (inspired by Social Choice Theory) are discussed in [3]. For instance, one could average the ratings of the individuals to obtain a group rating (making E and F the most preferred items by the group): the Average Strategy. One could take the minimum of the ratings, assuming that a group is as happy as its least happy member: the Least Misery Strategy. One could use a combination of the Average and Least Misery strategy, taking the average of ratings but only for those items whose ratings are all above a threshold: The Average Without Misery Strategy. We conducted a series of experiments in the context of a group recommender system to investigate which strategy is best (see [3] for details).

In Experiment 1, we investigated how people would solve this problem, so given ratings for individuals (as in Table 1), which items they thought should be presented to the group, if there was time for say six items. We compared our subjects’ decisions (and rationale) with those of the aggregation strategies. We found that humans care about fairness, and about preventing misery and starvation (“this one is for Mary, as she has had nothing she liked so far”). Subjects’ behaviour reflected that of several of the strategies (e.g. Average, Least Misery, and Average Without Misery were used), while other strategies were clearly not used.

In Experiment 2, we presented subjects with item sequences chosen by the aggregation strategies. Subjects rated how satisfied they thought the group members would be with those sequences, and explained their ratings. We found that the Multiplicative Strategy (which multiplies the individual ratings) performed best, in the sense that all subjects thought its sequence would keep all members of the group satisfied. Several strategies could be discarded as they clearly were judged to result in misery for group members. We also compared the subjects’ judgements with predictions by simple satisfaction modelling functions. Amongst other, we found that more accurate predictions resulted from using quadratic ratings, which e.g. makes the difference between a rating of 9 and 10 bigger than that between a rating of 5 and 6.

We also investigated how to deal with the order of a sequence, but this clearly needs more work in a learning context. Some findings are likely to be applicable here as well. For instance, it is likely that the motivation and confidence produced by a previous activity will affect a learner’s judgement of the next activity. Also, the performance of the learners will need to be taken into account when selecting the next activity.

When adapting to a group of learners, you cannot give everybody what is good for them all of the time. However, you do not want anybody to get too dissatisfied. For instance, in a class it would be bad if a learner were to leave and never come back, because they got really demotivated. An ideal teacher would adapt to the learners in such a way that they get activities that are really good for them most of the time. To achieve this, it is unavoidable that learners will occasionally get activities that are less appropriate, but this should happen at a moment when they can cope with it (e.g. when being in a good mood because they loved the previous activities). Therefore, it is important to monitor continuously the affective state of each learner. Rather than using self-ratings (which can be tedious for learners) or measuring (sensors are intrusive and not that good yet), it would be nice if we could predict it. In [4], we investigated different ways to model affective state. We compared the predictions of these models with the predictions of users. We also performed an experiment in an educational domain to compare the predictions with the real feelings of users.

Group adaptation techniques can also be used when adapting to an individual learner. Multiple criteria play a role when deciding on the next activity for a learner. For instance, its difficulty level, how suited it is with respect to learning style, how engaging it is, etc. Selecting an activity then may well resemble the situation described in Table 1, except that now Peter, Jane and Mary will be replaced by criteria. We have done some research on this problem (in a news domain), and found that the techniques are applicable, though weights need to be added to model the relative importance of criteria [5]. Group adaptation can also help to overcome the cold-start problem [6]: when you do not know much yet about a new learner, you can select activities for them that would keep the group of existing learners happy.

References